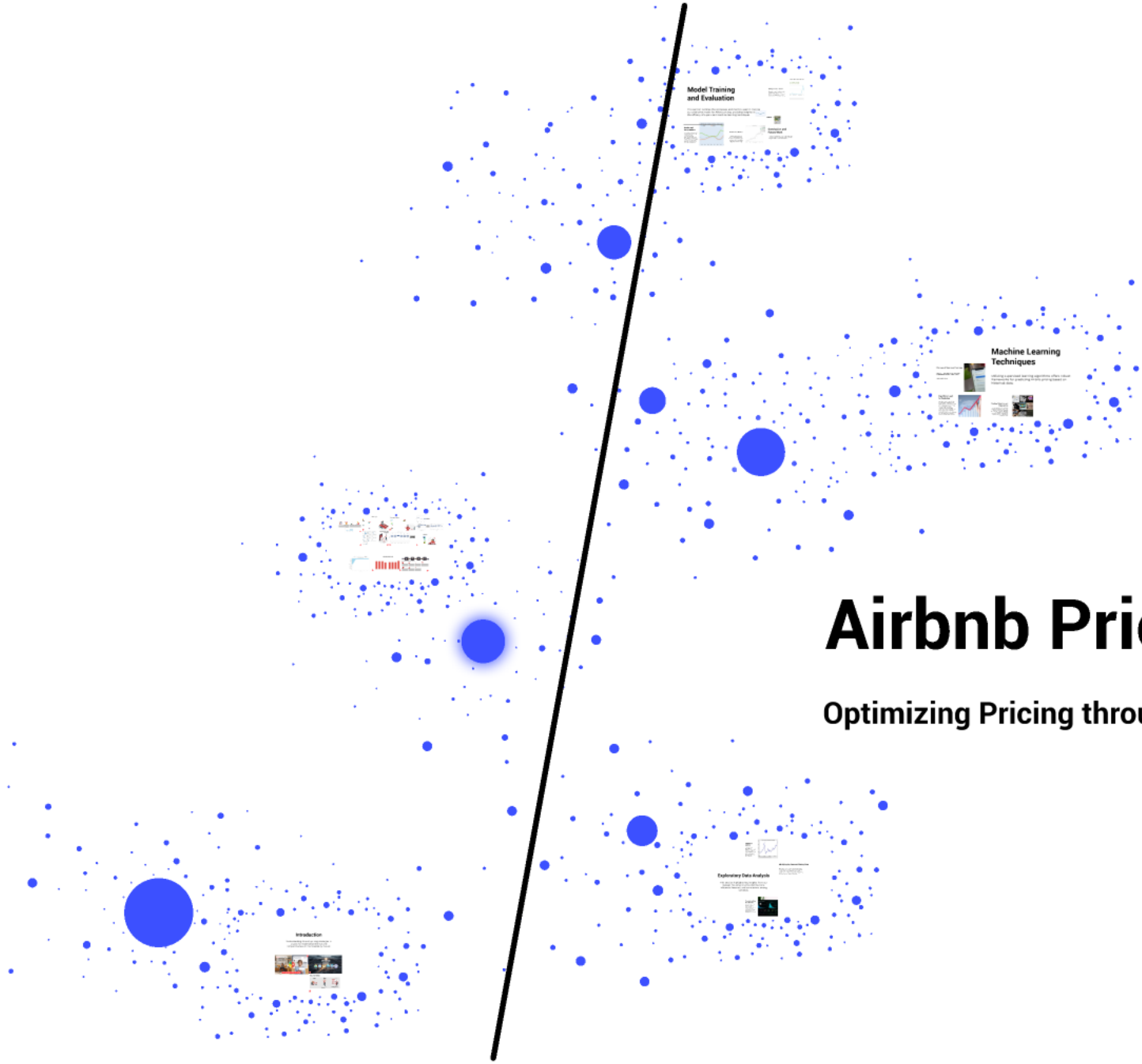
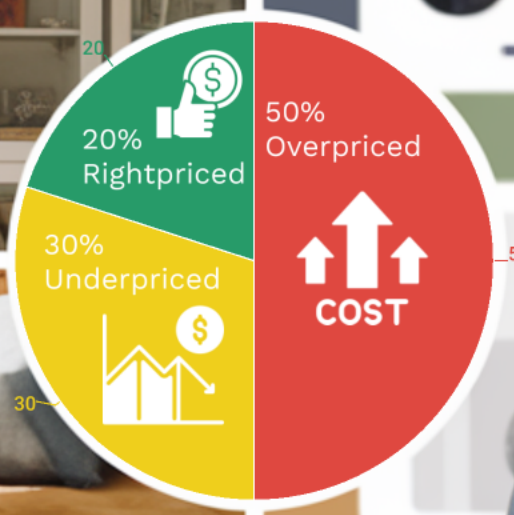


Airbnb Price Prediction

Optimizing Pricing through Supervised Machine Learning

$12 billion in revenue lost annually

Revenue
Down 60%



Pricing Chaos in Airbnb Listings

Why This Matters

Hosts

Maximize **Revenue** and minimize **Uncertainty**

Guests

Gain **transparency** and **affordability**

Airbnb

Build **trust** and strengthen **market competitiveness**

74% of Airbnb hosts are individuals relying on income consistency

Fair pricing increases bookings by **15%** on average

Data Description

74,111 Airbnb listings

6 major cities


New York


Boston


Chicago


Los Angeles

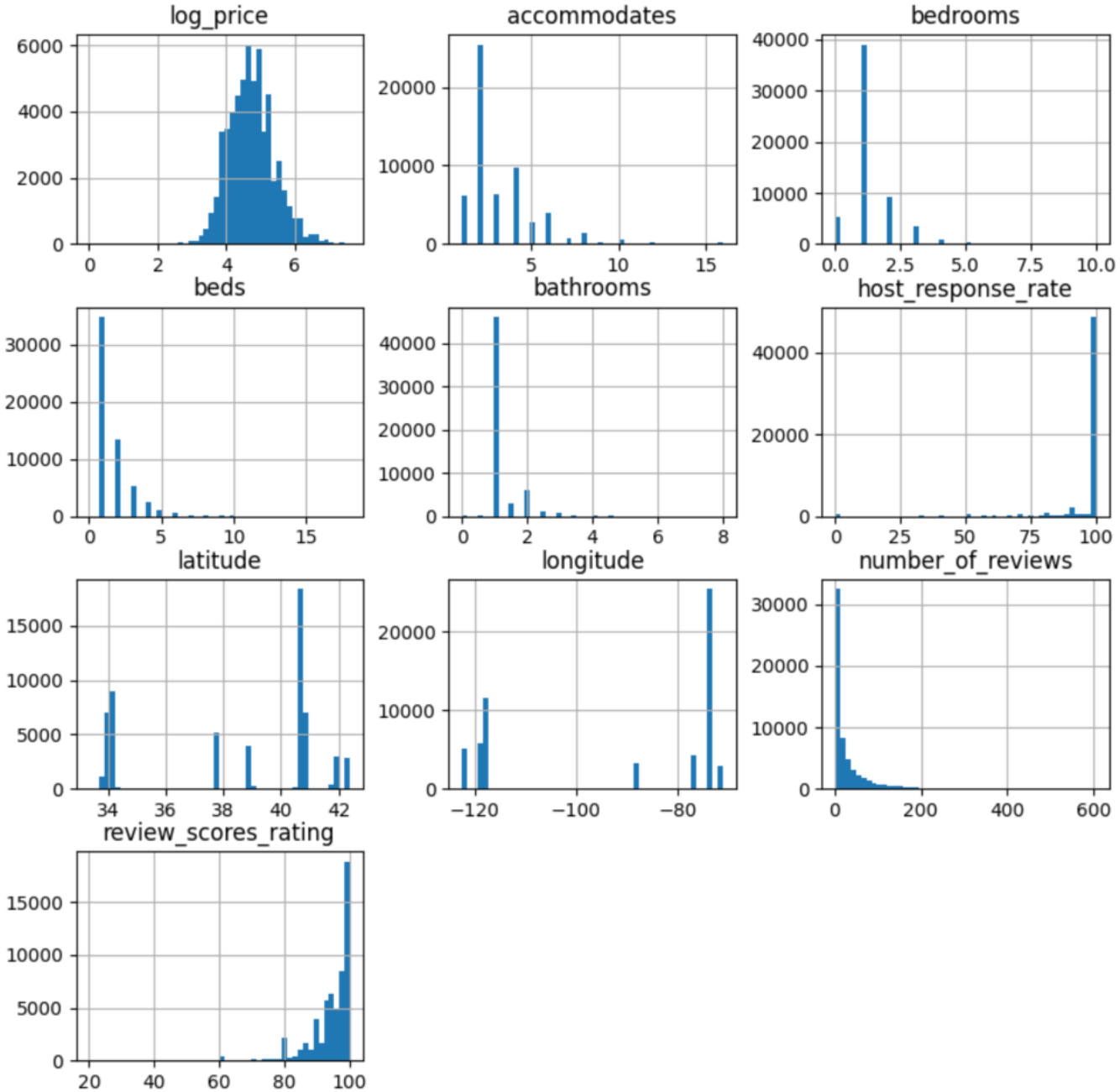

San Francisco


DC

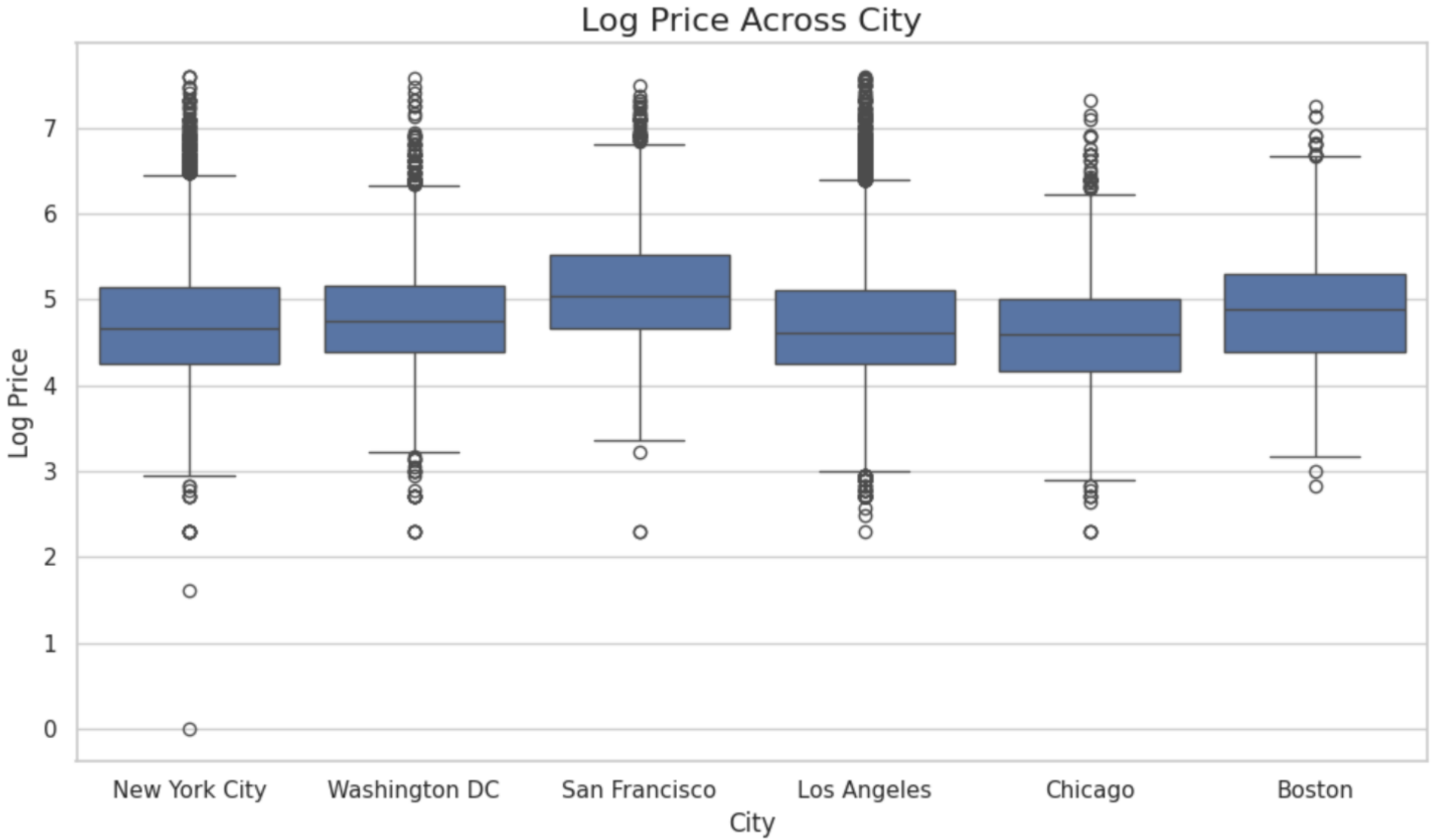
29 features

Key features include:
Room type: Entire home, private room, shared space.
City: SF, NYC, LA, Boston, Chicago, DC.
Accommodates, latitude, longitude.

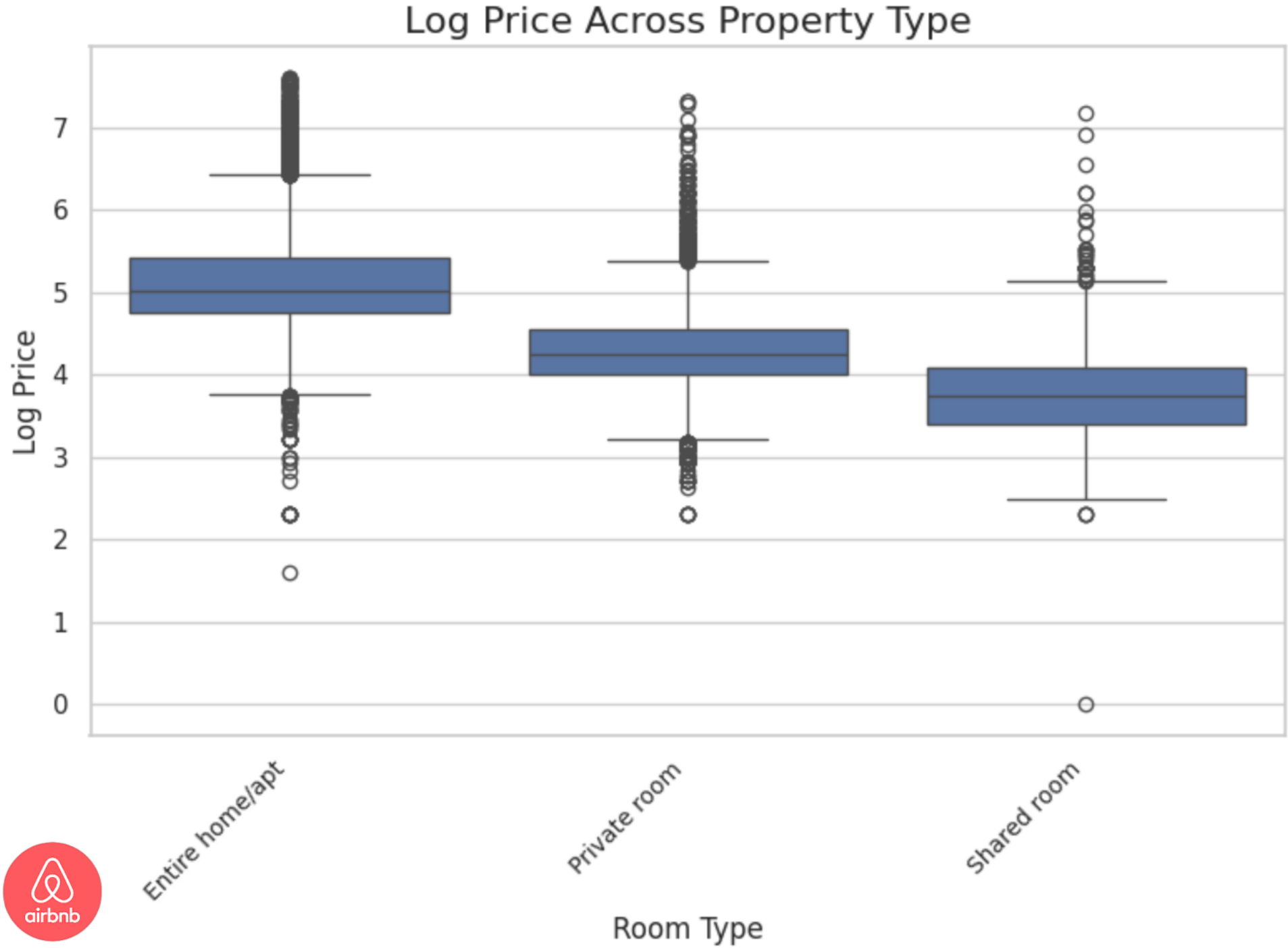
Exploratory Data Analysis



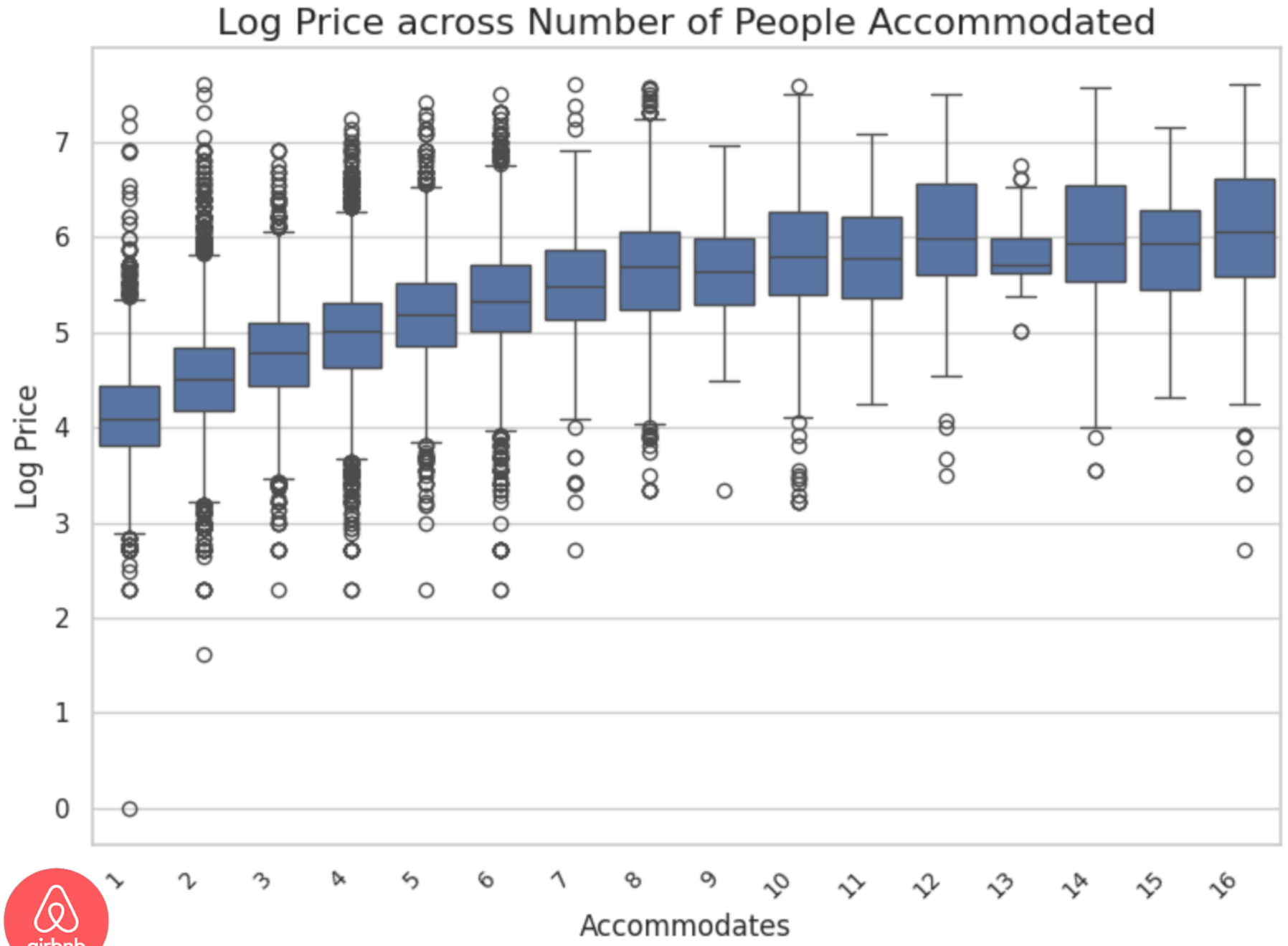
Log-transformation normalizes price distribution, reducing skew



Median prices in SF, Boston and NYC are higher



Entire homes have the highest median prices



Linear trend shows ~20% price increase per additional guest capacity


Log Price Across Property Type
Log Price
0
1
2
3
4
5
6
7
Apartment
Condominium
House
Loft
Townhouse
Hostel
Guest suite
Bed & Breakfast
Bungalow
Guesthouse
Dorm
Other
Camper/RV
Villa
Boutique hotel
Timeshare
In-law
Boat
Serviced apartment
Castle
Cabin
Treehouse
Tipi
Tent
Hut
Vacation home
Chalet
Yurt
Earth House
Train
Cave
Island
Property Type

Data Preprocessing for Airbnb Price Prediction

1. Pipeline Introduction
A robust preprocessing pipeline was built to address data inconsistencies and improve feature representation for the Airbnb price prediction model.

2. Boolean Feature Transformation
Columns such as instant_bookable and cleaning_fee were transformed by replacing 't'/'f' with 1/0. A custom transformer was created for future scalability.

3. Numerical Features Standardization
StandardScaler was applied to numerical columns like accommodates and bedrooms to ensure consistency in scale, preventing large values from skewing the model.

4. Categorical Features Encoding
TargetEncoder was used for columns like property_type to manage feature space efficiently, avoiding memory overhead while maintaining relationships with the target variable.

5. ColumnTransformer Integration
Combined various preprocessing methods into a single ColumnTransformer to streamline the pipeline, enhancing modularity and extensibility

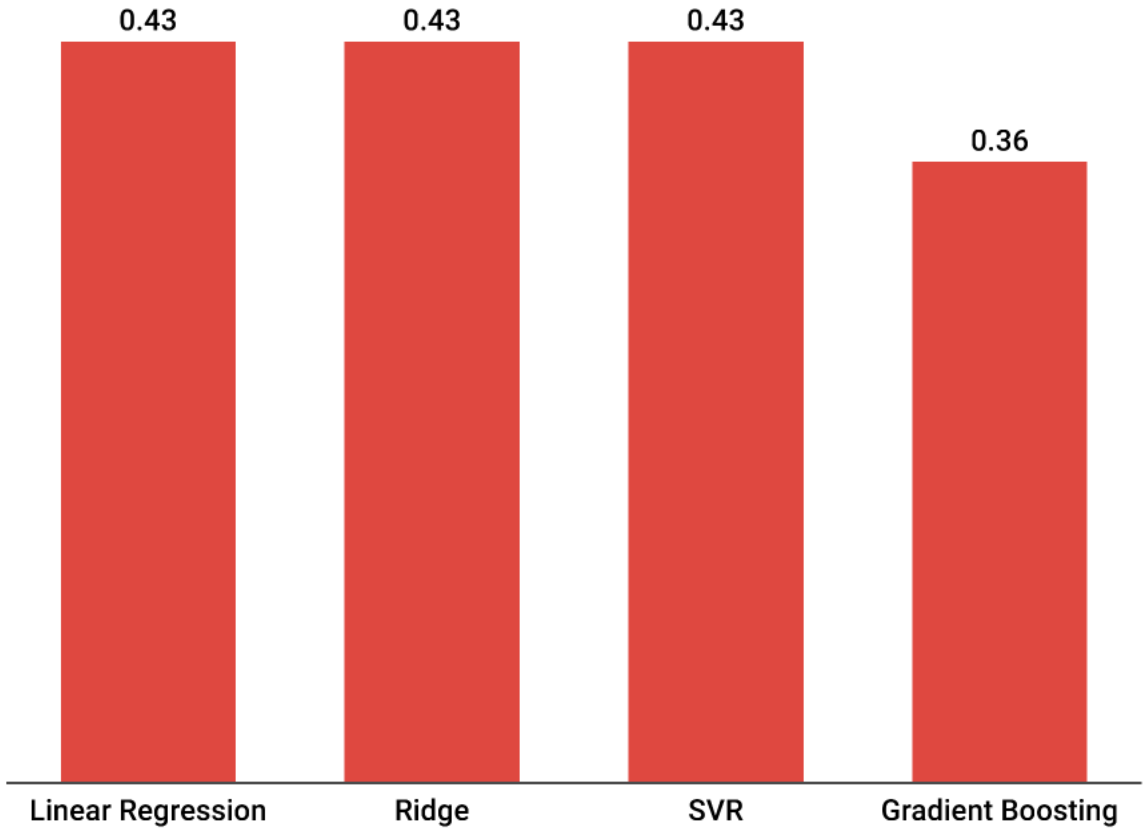
6. Pipeline Application
The pipeline was fitted on training data and transformed both training and test sets, ensuring consistent data shapes and performance evaluation.

7. Key Insights

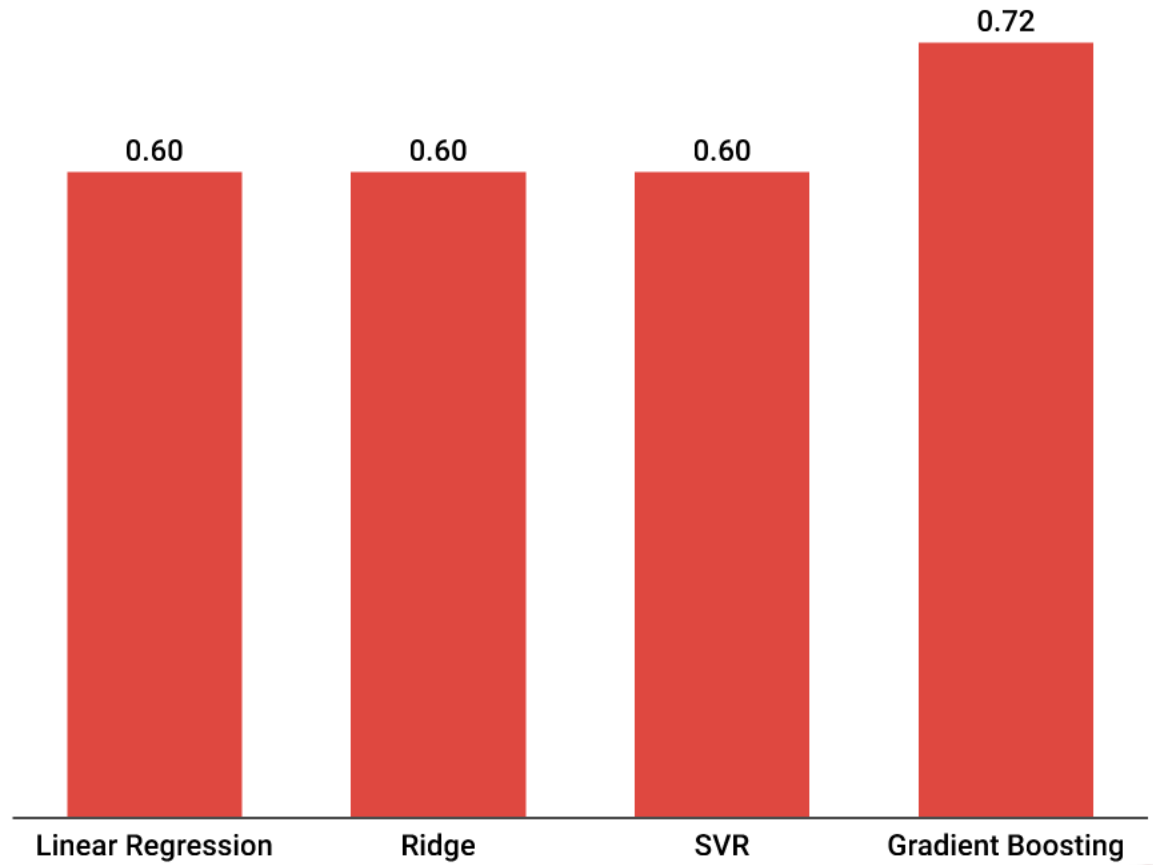
Avoiding OneHotEncoder minimized memory usage, while proper encoding and scaling contributed to improved model efficiency and convergence speed.

airbnb

Machine Learning Model Evaluation

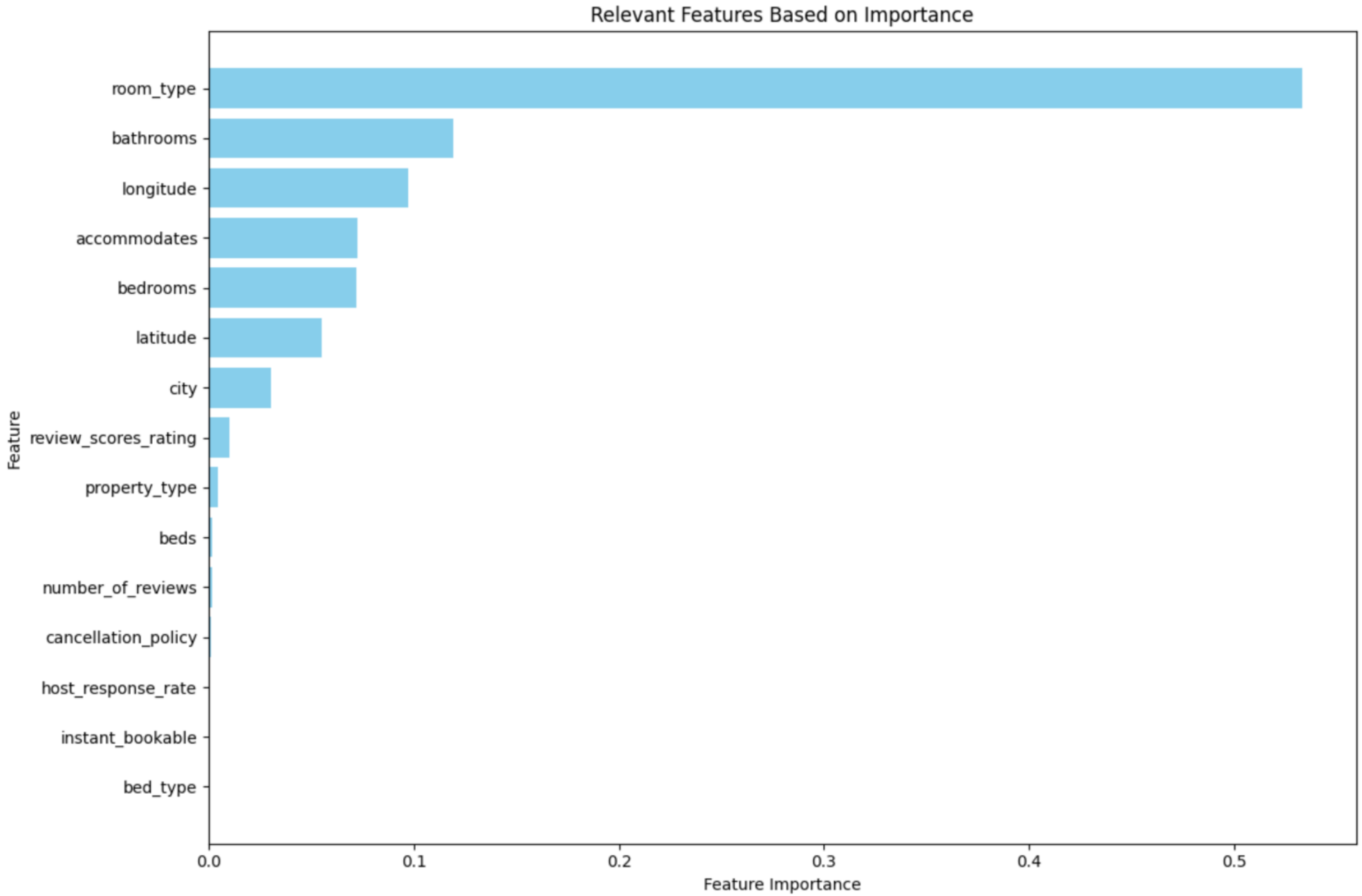


Comparison of RMSE Scores



Comparison of R^2 Scores

Feature Importance – Gradient Boosting Insights



Model Fine-Tuning

Hyperparameter Optimization with Randomized Search

01	learning_rate	0.1
02	max_depth	5
03	max_features	None
04	min_samples_leaf	1
05	min_samples_split	10
06	n_estimators	150
07	sub_sample	0.8

Model Evaluation & Final Results

Comprehensive Overview of Predictive Model Performance

Model Evaluation Metrics

Root Mean Square Error (RMSE) on training data is **0.33**, indicating a **strong fit**.
The **R^2 score of 0.76** highlights the model explains a significant portion of variance in the data.

Best Model

The Gradient Boosting Regressor was identified as the **best-performing model** based on evaluation metrics, demonstrating its robustness in capturing complex patterns in the data.

Test Predictions

Predictions made by the model show a **close alignment** with actual log prices, reinforcing the reliability of the model in real-world scenarios.
RMSE on test data is **0.34**, indicating a strong fit. **R^2 is 0.74**

Insight

By fine-tuning model parameters, we achieved **high accuracy** in predicting listing prices, successfully reducing prediction error by over **8.5%**.
This reflects the model's adaptability and effectiveness.

Challenges

Data Quality:

Addressing missing values, iNcoNsisTENT forMATS, and o u t l i e r s required significant effort.

Processing Time:

Parallel processing resolved delays caused by sequential cross-validation, improving computation time significantly

Scalability:

Ensuring computational efficiency for larger datasets remains a critical challenge

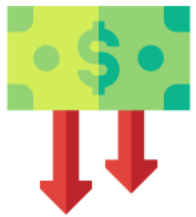
Recommendations

Empower Hosts with Data-Driven Insights:

Provide tools to help hosts analyze pricing trends and compare their listings against competitors.
Offer suggestions to optimize property descriptions and amenities for better appeal.

Leverage Geographical Insights:

Use clustering and ranking to recommend property optimizations and adjust pricing strategies by location.



Implement Advanced Pricing Strategies:

Introduce machine learning-driven pricing tools for dynamic adjustments based on:
Seasonality, demand, and competitor analysis.

Target Niche Segments:

Promote premium and unique listings through targeted marketing campaigns to attract high-value customers.

Future Steps

Enhanced Property Features:

Develop advanced ranking systems using zip code-based clustering and price normalization to identify growth opportunities.

Sentiment Analysis:

Examine customer reviews to extract sentiments and their impact on pricing and occupancy.

Expanding Dataset Scope:

Incorporate new variables like local events, weather conditions, and transportation access.

Demand Prediction and Seasonality:

Model seasonal trends using time-series data and optimize peak-period pricing dynamically.